IN THE UNITED STATES DISTRICT COURT
FOR THE SOUTHERN DISTRICT OF FLORIDA

GRACE, INC., *et al.*,

Plaintiffs,

v.

CITY OF MIAMI,

Defendant.

Case No. 1:22-cv-24066-KMM

EXPERT REPORT
Cory McCartan, Ph.D.
July 1, 2023

I. INTRODUCTION AND SCOPE OF WORK

1. My name is Cory McCartan, and I am a Data Science Assistant Professor / Faculty Fellow at the Center for Data Science at New York University. I specialize in the development and application of statistical methodology in the social sciences.

2. I have been retained by counsel representing the Plaintiffs to provide an analysis of population and compactness of Miami City Commission redistricting plans, including the Enjoined plan, the City's proposed remedial plan, the Plaintiffs' proposed remedial plan, and other alternative plans.

II. QUALIFICATIONS AND EXPERIENCE

3. I have a B.A. in mathematics from Grinnell College (2019) and an M.A. (2021) and Ph.D. (2023) from Harvard University in statistics. My research focuses on developing and applying

statistical methodology to problems in the social sciences. Specifically, I have extensively studied redistricting in the United States, publishing six peer-reviewed journal articles and working papers on redistricting in the last two years.

4. As part of my redistricting research agenda, I have developed a simulation algorithm that generates redistricting plans (McCartan and Imai, 2023). Part of this algorithm involves computing demographic, population, and compactness statistics for tens of thousands of randomly-drawn districts. The algorithm can be used to measure and evaluate existing redistricting plans along a variety of dimensions.

5. At Harvard, I also helped to start the Algorithm-Assisted Redistricting Methodology (ALARM) Project, which applies computational tools to study and evaluate redistricting plans and processes in the U.S. and around the globe.[1] One effort that I led as part of the ALARM Project involved collecting every congressional district drawn in the 2021-22 redistricting cycle, and generating over 200,000 algorithmic redistricting plans which complied with all relevant state laws and constitutions (McCartan et al., 2022). For each of the real-world and algorithmic plans, we calculated a battery of population, demographic, compactness, and partisan measures for each district, and released all of the plans and statistics to the public. These statistics included multiple different compactness metrics and the population overlap between each algorithmic district and the respective enacted district.

6. In 2021, I was hired to assist with algorithmic redistricting simulations for two court cases in the state of Ohio (Ohio Supreme Court Cases 2021–1193 and 2021–1449; both titled *League of Women Voters of Ohio v. Ohio Redistricting Commission*). As part of this work I computed measures of compactness, county splits, and demographics for various enacted, proposed, and

[1] Project website: https://alarm-redist.org/

remedial redistricting plans, along with 5,000 algorithmically simulated plans. These calculations and the accompanying algorithmic simulations provided evidence that the enacted plans in each case were statistical outliers as regards both partisan outcomes and traditional redistricting criteria such as compactness.

7. I have also developed and continue to maintain a variety of open-source software packages for using census data and studying redistricting plans. These tools can be installed for free on any personal computer and operating system. The packages include `redist` (Kenny et al., 2020), which implements several cutting-edge redistricting simulation algorithms, and an accompanying package `redistmetrics` (Kenny et al., 2021), which lets users calculate dozens of compactness, partisan, and demographic measures for redistricting plans. They also include `easycensus` (McCartan, 2023), `PL94171` (McCartan and Kenny, 2022), `alarmdata` (McCartan et al., 2023), and `tinytiger` (Kenny and McCartan, 2023), which provide access to Census data and geography shapefiles related to redistricting. Together, these software packages have been downloaded tens of thousands of times, and are widely used in academic research and by redistricting practitioners.

8. A copy of my curriculum vitae is attached as Exhibit A.

III. DATA, SOFTWARE, AND METHODOLOGY

9. I calculated compactness and population statistics for 8 plans, which are hereinafter abbreviated as follows:

- **2013**: the City's 2013 enacted plan;
- **Enjoined**: the City's 2022 enacted plan, enjoined by the Court;
- **City**: the City's final proposed remedial plan, adopted June 14, 2023 (counsel provided two

files for this plan: "City Enacted" and "City Opposing Counsel," as discussed in Part IV below);

- **P4**: the Plaintiffs' proposed remedial plan; and
- **P1–P3**: prior plans proposed by Plaintiffs.

10. Counsel representing the Plaintiffs provided me the geographic boundaries for all 8 plans as Block Assignment Files (BAFs) in comma-delimited format (`.csv`). I verified that these files were properly formatted and translated to geographically contiguous city council districts.

11. I downloaded 2020 decennial census total population counts for every census block in the City of Miami from the U.S. Census Bureau's software interface. These total population counts are the same that are mandated by P.L. 94–171 and are used in congressional apportionment. I also downloaded geographic shapefile information for the blocks.

12. I calculated four compactness measures for each plan: the Polsby-Popper score (Polsby and Popper, 1991), the Reock score (Reock, 1961), the Convex Hull score (ratio of the area of each district to the area of the district's convex hull), and the Edge-Cut score (see Dube and Clark, 2016, and McCartan and Imai (2023)). This latter measure is graph-theory based and is much less sensitive than other measures to particularities of local geography such as irregular coastlines and city boundaries. As such, it has recently gained traction among algorithmic and computational redistricting researchers. The calculations were carried out with the aforementioned `redistmetrics` software, which has been numerically validated and extensively tested.

13. I also calculated the degree to which each plan's districts overlap with the districts in the Enjoined and 2013 plans. To do so, I used population overlap routines implemented in my `redist` software, using the 2020 decennial census population data described above.

IV. ACCURACY OF BLOCK ASSIGNMENT FILES

14. Counsel representing Plaintiffs also provided me a slideshow presentation containing maps of various plans considered by the Miami City Commisison and asked me to identify any differences between the "D3 alt map v3" map on slide 6 and the final plan provided by the opposing counsel ("City Opposing Counsel"). I generated my own district map of the BAF provided by opposing counsel and compared it to the "D3 alt map v3" map.

15. I identified a discrepancy between the BAF provided by the opposing counsel and the "D3 alt map v3" map on the slide on the boundary between District 3 and District 2. Specifically, the "D3 alt map v3" map assigns census blocks 120860067201002 and 120860066051000 to District 3, while the BAF provided by opposing counsel assigns those blocks to District 2. In contrast, the "City Enacted" plan assigns these blocks to District 3, matching the "D3 alt map v3" in the slideshow.

16. The two blocks are not populated, and thus the discrepancy does not impact the population overlap analysis in Part VI.

V. COMPACTNESS OF REDISTRICTING PLANS

17. The Polsby-Popper scores are reported in Table 1 for each district of each plan. All values were multiplied by 100, so they lie on a 0–100 scale, for interpretability. Higher values indicate more compact districts.

Table 1: Polsby-Popper compactness scores.

Plan	District 1	District 2	District 3	District 4	District 5
2013	25	28	62	24	29
Enjoined	21	26	41	22	30
City Enacted	19	26	34	22	28
City Opposing Counsel	19	26	37	22	28
P1	24	39	77	34	55
P2	41	34	55	39	51
P3	35	31	54	39	43
P4	32	31	57	38	40

18. The Reock scores are reported in Table 2. All values were multiplied by 100, so they lie on a 0–100 scale. Higher values indicate more compact districts.

Table 2: Reock compactness scores.

Plan	District 1	District 2	District 3	District 4	District 5
2013	20	32	60	23	33
Enjoined	21	30	47	24	34
City Enacted	21	30	43	24	33
City Opposing Counsel	21	30	43	24	33
P1	18	36	66	33	61
P2	34	37	35	29	54
P3	30	34	35	29	47
P4	31	34	37	28	47

19. The convex hull scores are reported in Table 3. All values were multiplied by 100, so they lie on a 0–100 scale. Higher values indicate more compact districts.

Table 3: Convex hull compactness scores.

Plan	District 1	District 2	District 3	District 4	District 5
2013	67	65	84	61	61
Enjoined	58	63	71	53	65
City Enacted	58	63	67	54	62
City Opposing Counsel	58	63	67	54	62
P1	64	80	94	71	85
P2	72	71	90	87	82
P3	67	66	89	87	75
P4	66	66	92	86	75

20. The Edge-Cut measure is reported in Table 4 for each plan. This measure is plan-wide and not district-specific. It counts the number of pairs of neighboring census blocks which are separated by a district line. In contrast with the above measures, *lower* values indicate more compact districts.

Table 4: Edge-Cut measure by plan. Lower values indicate more compact plans.

Plan	Edges cut by district boundaries
2013	342
Enjoined	420
City Enacted	400
City Opposing Counsel	398
P1	168
P2	184
P3	248
P4	237

VI. POPULATION OVERLAP BETWEEN REDISTRICTING PLANS

21. I first calculated the overlap between districts in the Enjoined plan to corresponding districts in the City and P1–P4 plans. These calculations are summarized in Tables 5 (percentage overlap) and 6 (raw population counts). Because the two blocks that differ between both provided versions of the City plan ("City Enacted" and "City Opposing Council") are not populated, these

two versions have identical overlap calculations; they are reported together as "City" below.

Table 5: District population overlap between Enjoined and various other plans, expressed as a percentage of the population of each plan's corresponding district.

	Overlap with...					
Enjoined plan	Enjoined	City	P1	P2	P3	P4
District 1	100	98.2	61.1	56.7	54.8	53.3
District 2	100	92.2	63.3	89.5	96.7	96.7
District 3	100	90.6	83.5	45.4	46.0	47.1
District 4	100	94.8	56.9	42.7	42.7	44.0
District 5	100	94.7	84.1	85.8	94.0	92.5
Districts 1, 3, and 4	100	97.8	77.0	48.7	48.8	49.3
Overall	100	94.1	69.8	64.3	66.9	67.0

Table 6: District population overlap between Enjoined and various other plans.

	Overlap with...					
Enjoined plan	Enjoined	City	P1	P2	P3	P4
District 1	88,108	85,892	52,916	49,042	48,043	46,690
District 2	93,300	82,563	56,388	80,476	86,533	86,533
District 3	87,658	80,842	73,237	38,662	39,527	41,383
District 4	86,597	84,861	50,699	38,554	38,554	38,554
District 5	86,578	81,843	75,561	77,483	83,418	82,981
Districts 1, 3, and 4	262,363	251,595	176,852	126,258	126,124	126,627
Overall	442,241	416,001	308,801	284,217	296,075	296,141

22. I then calculated the overlap between districts in the 2013 plan to corresponding districts in the Enjoined, City, and P1–P4 plans. These calculations are summarized in Tables 7 (percentage overlap) and 8 (raw population counts). Because the two blocks that differ between both provided versions of the City plan are not populated, these two versions have identical overlap calculations; they are reported together as "City" below.

Table 7: District population overlap between 2013 and various other plans, expressed as a percentage of the population of each plan's corresponding district.

	Overlap with...					
2013 plan	Enjoined	City	P1	P2	P3	P4
District 1	92.1	92.1	53.4	49.0	48.4	48.4
District 2	100.0	98.1	78.4	100.0	100.0	100.0
District 3	91.5	83.8	83.5	45.4	46.0	45.5
District 4	86.0	84.6	63.8	49.4	49.4	49.4
District 5	87.5	88.4	79.5	81.3	85.9	86.0
Districts 1, 3, and 4	97.5	96.3	79.0	51.9	52.3	51.9
Overall	91.5	89.4	71.8	65.4	66.1	66.1

Table 8: District population overlap between 2013 and various other plans.

	Overlap with...					
2013 plan	Enjoined	City	P1	P2	P3	P4
District 1	81,120	80,553	46,257	42,383	42,383	42,383
District 2	93,300	87,891	69,873	89,897	89,522	89,522
District 3	80,169	74,737	73,237	38,662	39,527	39,999
District 4	74,504	75,749	56,796	44,651	44,651	43,267
District 5	75,753	76,398	71,427	73,419	76,232	77,156
Districts 1, 3, and 4	235,793	231,039	176,290	125,696	126,561	125,649
Overall	404,846	395,328	317,590	289,012	292,315	292,327

23. At the request of counsel for the Plaintiffs I also calculated the overlap for the grouped set of Districts 1, 3 and 4. These are reported as a separate summary line in Tables 5–8.

Cory McCartan

Cory McCartan, Ph.D.
July 1, 2023

REFERENCES

Dube, M. P. and Clark, J. T. (2016). Beyond the circle: Measuring district compactness using graph theory. In *Annual Meeting of the Northeastern Political Science Association*.

Kenny, C. T. and McCartan, C. (2023). *tinytiger: Lightweight Interface to TIGER/Line Shapefiles*. https://cran.r-project.org/package=tinytiger.

Kenny, C. T., McCartan, C., Fifield, B., and Imai, K. (2020). *redist: Computational Algorithms for Redistricting Simulation*. https://CRAN.R-project.org/package=redist.

Kenny, C. T., McCartan, C., Fifield, B., and Imai, K. (2021). *redistmetrics: Redistricting Metrics*. https://CRAN.R-project.org/package=redistmetrics.

McCartan, C. (2023). *easycensus: Quickly Find, Extract, and Marginalize U.S. Census Tables*. https://cran.r-project.org/package=easycensus.

McCartan, C. and Imai, K. (2023). Sequential Monte Carlo for sampling balanced and compact redistricting plans. *Annals of Applied Statistics*, Accepted.

McCartan, C. and Kenny, C. T. (2022). *PL94171: Tabulate P.L. 94-171 Redistricting Data Summary Files*. https://cran.r-project.org/package=PL94171.

McCartan, C., Kenny, C. T., Simko, T., Garcia III, G., Wang, K., Wu, M., Kuriwaki, S., and Imai, K. (2022). Simulated redistricting plans for the analysis and evaluation of redistricting in the united states. *Scientific Data*, 9(1):689.

McCartan, C., Kenny, C. T., Simko, T., Zhao, M., and Imai, K. (2023). *alarmdata: Download, Merge, and Process Redistricting Data*. https://github.com/alarm-redist/alarmdata/.

Polsby, D. D. and Popper, R. D. (1991). The third criterion: Compactness as a procedural safeguard against partisan gerrymandering. *Yale Law & Policy Review*, 9(2):301–353.

Reock, E. C. (1961). A note: Measuring compactness as a requirement of legislative apportionment. *Midwest Journal of Political Science*, 5(1):70–74.

EXHIBIT A

Curriculum Vitae

Cory McCartan

Curriculum Vitae

June 2023

Contact Information
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Employment

The Pennsylvania State University Expected 2024
Assistant Professor of Statistics

New York University 2023 – 2024
Center for Data Science
Data Science Assistant Professor / Faculty Fellow

Education

Harvard University 2019 – 2023
Ph.D., Statistics, 2023. Advisor: Kosuke Imai.
A.M., Statistics, 2021.

Grinnell College 2015 – 2019
B.A., Mathematics, with honors.

Publications

"Sequential Monte Carlo for Sampling Balanced and Compact Redistricting Plans," with Kosuke Imai. *Annals of Applied Statistics*, Forthcoming.

Covered by the Washington Post, Quanta Magazine.

"Widespread Partisan Gerrymandering Mostly Cancels Nationally, but Reduces Electoral Competition," with Christopher Kenny, Tyler Simko, Shiro Kuriwaki, and Kosuke Imai. *Proceedings of the National Academy of Sciences* 120:25 (2023).

"Recalibration Of Predicted Probabilities Using the 'Logit Shift': Why does it work, and when can it be expected to work well?" with Evan T. R. Rosenman and Santiago Olivella. *Political Analysis* 1-11 (2023).

"Comment: The Essential Role of Policy Evaluation for the 2020 Census Disclosure Avoidance System" with Christopher T. Kenny, Shiro Kuriwaki, Tyler Simko, Evan T. R. Rosenman, and Kosuke Imai. *Harvard Data Science Review*, Special Issue 2 (2023).

"Simulated Redistricting Plans for the Analysis and Evaluation of Redistricting Plans in the United States," with Christopher Kenny, Tyler Simko, Shiro Kuriwaki, George Garcia III, Kevin Wang, Melissa Wu, and Kosuke Imai. *Scientific Data* 9:689 (2022).

"The Use of Differential Privacy for Census Data and its Impact on Redistricting: The Case of the 2020 U.S. Census," with Christopher T. Kenny, Shiro Kuriwaki, Tyler Simko, Evan T. R. Rosenman, and Kosuke Imai. *Science Advances* 7:41 (2021).

Covered by the Associated Press, the Washington Post, the San Francisco Chronicle, and others.

"Geodesic Interpolation on Sierpinski Gaskets," with Caitlin M. Davis, Laura A. LeGare, and Luke G. Rogers. *Journal of Fractal Geometry* 8:2 (2021).

Working Papers

"Estimating Racial Disparities When Race is Not Observed," with Jacob Goldin, Daniel E. Ho, and Kosuke Imai.

"Individual and Differential Harm in Redistricting," with Christopher T. Kenny.

"Measuring and Modeling Neighborhoods," with Jacob R. Brown and Kosuke Imai. Under Review.

"Evaluating Bias and Noise Induced by the U.S. Census Bureau's Privacy Protection Methods," with Christopher T. Kenny, Shiro Kuriwaki, Tyler Simko, and Kosuke Imai.

"Making Differential Privacy Work for Census Data Users," with Tyler Simko and Kosuke Imai.

"Finding Pareto Efficient Redistricting Plans with Short Bursts."

Works in Progress

"Studying Officeholders' Perceived Geographic Constituencies," with Jacob R. Brown and Hunter E. Rendleman.

"Regression of the Conditional Median," with Xiao-Li Meng.

"Algorithm-Assisted Redistricting Methodology" (book), with Kosuke Imai, Christopher Kenny, and Tyler Simko.

Other Writing

"Researchers need better access to US Census data," with Tyler Simko and Kosuke Imai. *Science*, 380:6648 (2023).

"Candy cane shortages and the importance of variation." International Statistical Institute: *Statisticians React to the News* (December 21, 2021).

"Where will the rocket land?" International Statistical Institute: *Statisticians React to the News* (May 12, 2021).

"Who's the most electable Democrat? It might be Warren or Buttigieg, not Biden." *The Washington Post* (October 23, 2019).

"I-405 Express Toll Lanes: Usage, benefits, and equity," with Shirley Leung, C.J. Robinson, Kiana Roshan Zamir, Vaughn Iverson, and Mark Hallenbeck. Technical report for the Washington State Department of Transportation (2019).

Software

`redist`: Simulation Methods for Legislative Redistricting

`redistmetrics`: Redistricting Metrics

`easycensus`: Quickly Find, Extract, and Marginalize U.S. Census Tables

`birdie`: Bayesian Instrumental Regression for Disparity Estimation

`causaltbl`: Tidy Causal Data Frames and Tools

`PL94171`: Tabulate P.L. 94-171 Redistricting Data Summary Files

adjustr: Stan Model Adjustments and Sensitivity Analyses using Importance Sampling

conformalbayes: Jackknife(+) Predictive Intervals for Bayesian Models

alarmdata: Download, Merge, and Process Redistricting Data

blockpop: Estimate Census Block Populations for 2020

ggredist: Scales, Palettes, and Extensions of `ggplot2` for Redistricting

tinytiger: Lightweight Interface to TIGER/Line Shapefiles

wacolors: Colorblind-friendly Palettes from Washington State

Presentations

Joint Statistical Meetings, Invited Paper Panel: 2022, 2021.

Society for Political Methodology, Annual Meeting, Paper: 2022; Poster: 2022, 2021.

American Association for Public Opinion Research, Annual Meeting, Poster: 2022.

Institute for Quantitative Social Science, Harvard University, Applied Statistics Workshop, Paper: 2023, 2022, 2021, 2020.

Teaching

Harvard University

STAT 117: Introduction to Biostatistics *Awarded a Certificate of Distinction in Teaching*	Spring 2021
STAT 221: Monte Carlo Methods & Other Computational Tools for Statistical Learning	Fall 2020

Grinnell College

MAT 215: Linear Algebra	Fall 2017 and Spring 2019
MAT 310: Statistical Modeling	Fall 2018
Grinnell College Math Lab	2018 – 2019

Honors and Awards

Best Statistical Software Award, for developing statistical software that makes a significant research contribution, awarded to the `redist` software package by the Society for Political Methodology, 2022.

Service

Harvard Statistics Graduate Council — 2020 – 2023
Organized Ph.D. student retreat and research "lightning talks," 2020 and 2021.

First-year Ph.D. Student Mentor — 2020 – 2023

Harvard Graduate Students Union – UAW Local 5118 — 2019 – 2021
Elected member, Bargaining Committee, 2020–2021 and 2021–2024 contracts.
Interim chair, Finance and Benefits Committee, 2020.

Reviewer: *Election Law Journal, Sloan Foundation*.

Membership

American Statistical Association, Society for Political Methodology, American Political Science Association.

Other Experience

Data for Progress — 2022
Consultant, Midterm election modeling

American Civil Liberties Union of Ohio — 2021 – 2022
Consultant (with Prof. Kosuke Imai), *League of Women Voters of Ohio v. Ohio Redistricting Commission* (Ohio Supreme Court Cases 2021–1193 and 2021–1449).

University of Washington eScience Institute — Summer 2019
Data Science for Social Good Fellow

Union of Grinnell Student Dining Workers — 2016 – 2019
Founder, President (2016–17), and Advisor to the Executive Board (2018–19)

University of Connecticut — Summer 2018
REU Participant, Department of Mathematics

Fred Hutchinson Cancer Research Center — Summer 2017
Lead Intern, Department of Biostatistics

Grinnell College Department of Mathematics — 2017
Course Grader

Cray, Inc. — Summer 2015
Intern, Chapel language testing